MASTER

Perceived message understanding

on the positioning and orientation evaluations between differing interaction scenarios with an automated guided vehicle

Behrens, J.S.

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Perceived Message Understanding: on the positioning and orientation evaluations between differing interaction scenarios with an automated guided vehicle

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Abstract

Automated guided vehicles (AGVs) have been increasingly more common in distribution centers and airport terminals. Although there has been much research conducted on how AGVs navigate through these environments, there is much to be examined on how human operators in the environment see the navigation of those AGVs. One way an AGV can display its trajectory to an operator, is through the use of explicit social cues, such as speech and signalling. However, often these cues are misunderstood or take a long time to be registered by the human, causing discomfort. Another way in which an AGV can display where it is proceeding towards, is through the use of human aware navigation through a trajectory. In this thesis, we used two different navigation methods (minimum jerk versus shortest path trajectories) to examine which type of trajectory performs better in terms of the positioning understanding (knowing to which point the robot will navigate to) and orientation understanding (knowing in which angle the robot will end up in). These understandings were implicitly measured by checking how fast and accurate the operator was and explicitly measured by letting the operator evaluate whether they understood the robot through questionnaires. 27 participants partook in a two-way (trajectory type: minimum jerk vs. shortest path) within-subjects design lab study. This study found that positioning accuracy was significantly higher for minimum jerk trajectories, while orientation accuracy was significantly higher for shortest path trajectories. These results and additional effects were discussed. Hence, we concluded that the navigational behavior of the robot can be used as an alternative interaction cue, showing where the robot is heading towards, and that dependent on the environment cues and personal preferences or tasks, the effect of different trajectory types may differ.

Contents

Introduction

The practice of implementing automated guided vehicles (AGVs) in sortation centers and airport terminals has been expanding since the early 2000s (IFR, 2018). Due to this increase, a transition has been taking place from environments which are mainly designed around human factors, towards environments which are designed to keep both human and robotic factors in mind. However, this transition seems to be progressing rather slowly. This slow pace can be explained by the fact that companies have policies which enforce that distributive operations should either exclusively be performed on a human-oriented scale (mostly reliant on the use of manned forklifts) or an automation-oriented scale (mostly reliant on AGVs or robotics picking up one product to drop it off somewhere else). In turn, this distinction can be attributed to the severe safety regulations, usually physically separating the operators from the robotics. Therefore, this separation enforces the idea that humans and robotics should only interact indirectly, usually done through some kind of mediation device. This indirect interaction is likely to increase idle times for both human and robotics, which was shown to decrease productivity (Nikolaidis, Ramakrishnan, Gu, & Shah 2015). Moreover, due to the enforcement of less direct contact, little knowledge is gained on the goals of the robot by the human and vice versa.

Fortunately, over the last decade numerous projects have been conducted, showing the theoretical, increased benefits personal Human-Robot Interaction (HRI) in shared workspaces (Michalos, Makris, Tsarouchi, Guasch, Kontovrakis & Chryssolouris 2015). These interaction forms show increased benefits for both company goals such as an increase in productivity (Ding, Schipper & Matthias, 2014), as well as human perception of safety and comfort (Butler & Agah, 2001; Lasota, Rossano & Shah, 2014). When we want to maximize these positive effects, it becomes clear that we need a more intricate understanding on how different kinds of users interact with different kinds of robotics. Since, it was

shown that if we want HRI to truly aid effective collaboration, gestures and cues from both sides need to be understood (Liu & Wang, 2018 for an overview). In this paper, we will regard how manipulating an interaction form with an AGV, can influence this understanding.

Application of AGVs

The concept of an AGV navigating through an industrial environment has been established as early as 1968 (Hart, Nilsson & Raphael, 1968). In this paper, a simple algorithm was developed on which a robot (called Shakey the Robot) could find a cost-effective trajectory in an environment littered with obstacles. Though innovative, it can hardly be stated that through this obstacle avoidance algorithm the robot was truly autonomous, since it was still restricted to a predefined path. In a similar approach, Arkin and Murphy (1990) studied the effect of automatic guided vehicles in the workplace. The authors saw that when a vehicle is restricted to a predefined track to move around on, it was not able to show interaction with the environment. They noted that interaction to the environment can be coerced by introducing an automated robot with actively updated knowledge of the world surrounding it, in order to avoid unmodeled obstacles. Through this system, the robot was able to show in which direction it was proceeding to move. This relation the robot had to its environment, was able to show that the robot was able to autonomously navigate without restricting other activities in that environment.

In more recent times, most HRI is either established in the 'factory' or 'home' setting. In the factory setting, there usually is a clear physical separation between the human and the robot, whereas in the home setting the robot is seen as a social presence, with an emphasis on interaction through social cues (Sisbot, Marin-Urias, Broquère, Sidobre & Alami, 2010). There thus seems to be a paradigm for the distinction between working and living robots. This distinction establishes a grey area in the middle, for which the interaction factors between human and robot are still largely unknown. Most recent work

focuses on interaction forms where the robot gets more of a social presence in the factory environment, and the forms where the robot becomes less of a social presence in the home environment. The HRI in these environments requires to be more intently researched, especially when we consider the areas where there is a substantial reliance on the aid of AGVs for operators in distribution and sortation centers and in airport baggage handling (Bøgh, Hvilshøj, Kristiansen & Madsen, 2012). In a paper by Lenior (2012), it was shown that with the aid of the right human and robotic design factors, AGVs can be implemented in airport halls such that they efficiently interact with the human operators in that environment.

This paradigm can potentially be applied to the FLEET robot, developed by Vanderlande (van Meijl & van Eekelen, 2016), of which an example is shown in Figure 2. These robots behave as AGVs that are programmed to navigate through a distribution floor, picking up and delivering packages. through their shuttle-based AGV design, these AGVs benefit that they can shorten travel time and distance for both storage and retrieval (Tappia, Roy & de Koster, 2016). Moreover, they decrease the need for locked conveyors, resulting in a more flexible and less time consuming system. Considering that there is a rising requirement for flexible space management, and higher fault tolerance, a system with these kind of AGVs its decentralized control architecture is quite recommendable. Furthermore, it was shown to open up many potential applications (Lima & Custodio, 2005). For instance, in a decentralized system with multiple AGVs, it is of great importance to acknowledge the effects of routing, which takes into account collision avoidance, where other AGVs crossing one AGV its trajectory are actively updated. This control approach was implemented to avoid small collisions which could result in deadlock situations, in which all AGVs are all indecisively waiting for another robot to move. These situations require external intervention to get resolved, thus greatly diminishing productivity (Silven, 2018). To avoid these situations, it is important that the operator of these AGVs is able to easily understand the

message being communicated by the AGV through its situated behavior. In summary, decentralization can lead to unpredictable behavior, altering the effects of communication between an AGV and an operator, and in order to support effective communication, AGVs need to be clear and effective in what their goal and trajectory is.

Figure 2: *Picture of a FLEET robot, developed by Vanderlande, carrying luggage. (Taken from https://www.vanderlande.com/news/fleet-all-systems-go-at-rotterdam/, 2020)*

AGV interaction cues

Humans often rely on non-verbal cues in all sorts of communication (Becchio, Sartori & Castiello, 2010). A substantial amount of HRI literature has shown a reflection of this general reliance, by implementing these cues in hand-over tasks (Huber, Rickert, Knoll, Brandt & Glasauer, 2008; Parastegari, Abbasi, Noohi & Zefran, 2017; Cakmak, Srinivasa, Lee, et al., 2011; Mainprice, Sisbot, Simeon & Alami, 2019), pointing tasks (Häring, Eichberg, & André, 2012; Quintero, Fomena, Shademan,

Wolleb, Dick & Jagersand, 2013) and social tasks (Glas, Satake, Ferreri, Kanda, Hagita & Ishiguro, 2013; Rodriquez-Lizundia, Marcos, Zalama, Gómez-García-Bermejo & Gordaliza, 2015) when regarding the cooperation between human and robot.

Moreover, it has been shown that using signaling behavior such as gaze direction or using turn indicators were both able to show where the robot was heading towards (May, Dondrup & Hanheide, 2015). In addition, Scheffer (2018) showed that using movement signals was as favorable as speech for factors such as social presence, perceived safety, and perceived message understanding. Moreover, in this paper, it was found that gestures were regarded to be a much faster interaction method, compared to speech. This might imply that the a robots behavior can be understood much faster with the usage of gestures, which is beneficial for natural HRI.

However, explicit signalling methods, such as speech, often require much understanding and attention to be accurately read. Because speech instructions take time to be translated by the operator, especially when the robot tries to communicate something relating to orientation (e.g.:'move to the left from my point of view'). Thus, we can assume that operators interacting with this robot might not always have the required understanding and attention to do this, especially when tending to physically or mentally challenging tasks. Moreover, it was found that changing a factor as minor as the speed with which the robot moves was shown to substantially increase mental activity and feelings of anxiety (Koppenborg, Nickel, Naber, Lungfiel & Huelke, 2017; MacArthur, Stowers & Hancock, 2017). Also, if one is attending to one task and needs to keep its visual focus there, one can not keep its visual attention on a robot, even when no interaction is taking place (Rossi, Santangelo, Ruocco, Ercolano, Raggioli & Savino, 2018). Thus there are multiple reasons as to why more implicit forms of HRI can be more appropriately applied to situations were both human and AGV are either occupied.

Human Aware Navigation Models

Much research has been conducted on the subject of AGVs adapted to avoid collisions with a human (Pandey & Alami, 2010; Lam, Chou, Chiang & Fu, 2011; Kruse, Basili, Glasauer & Kirsch, 2012; Koppenborg et al., 2017). However, it is not only important that the robot knows how to prevent collisions with humans and other obstacles in its environment, but also that the intent of where the robot wants to navigate towards is easily read humans in its environment.

There are several Human Aware Navigation (HAN) models of robot navigation that have kept human knowledge and preferences in mind, such as the Human Aware Interaction Planner (Sisbot, Marin-Urias, Alami & Simeon, 2007). This planner keeps the AGV trajectory on a specific path while keeping distance and social costs into account. This ensures that the AGV will be inside the field of view and within a safe distance of the human. In order to achieve this, the planner must consider a correct identification of human positioning and orientation in the environment, and the task being performed by the human. Another model is the Qualitative Trajectory Calculus, proposed by Hanheide, Peters, and Bellotto (2012), which regards a human's personal space as a probabilistic model. This model weighs the velocity vector based on distance and velocity of the humans, where this weight is also largely dependent on the kind of task the human and AGV are trying to complete (cooperative or competitive), and whether this task is based on whether or not the AGV is engaged in guiding the human or vice versa (Yuan, Twardon & Hanheide, 2010; Jevtić, Doisy, Parmet & Edan, 2015; Triebel, Arras, Alami, Beyer & Breuers, 2016).

In the study by Lichtenthäler, Lorenz, Karg and Kirsch (2012) several of the aforementioned HANs were tested on whether their trajectories were predictable according the operator. The predictability of an AGV was defined as the understanding of how the current trajectory of an AGV leads to a possible

destination. For the model in which the human was regarded as an obstacle (MB-DWA), predictability would be rated the highest by the operator. Meaning that an AGV with MB-DWA planning, would mainly show the navigation towards the end goal, in a way where the orientation and the position from the trajectory reflected a change towards the end position and orientation. These results were also found in the understanding of the operators, since they were able to infer the destination of the robot with high confidence, if the current trajectory and orientation of the robot was highly predictable.

In similarity to Lichtenthäler et al. (2012), Dragan, Lee, and Srinivasa (2013) defined the ease with which we can understand the navigation of an AGV towards a certain endpoint, dependent on the current trajectory, to be the legibility of the AGV. Contrary to this, predictability was defined as the ease at which we can understand the next displacement by the robot given the current trajectory. These definitions were used to test the legibility and predictability of differing limb movements of a robot. Dragan et al. (2013) concluded that a limb movement trajectory with high legibility would be paired with low predictability and vice versa. We can illustrate this finding with an example, which can be seen in Figure 3. When an AGV is programmed to drive around objects in a very wide margin and there is an object between it and its goal, we might see a very wide trajectory around the object, resulting in high understanding of the end orientation, and a high predictability. Since the angular velocity (the velocity with which the orientation changes) stays mostly constant during the trajectory and we can thus easily see in which orientation it is going to end up, we know what the endpoint is. However, when a robot deviates from the shortest path right from the start, it will presumably result in a low understanding of the end positioning, and thus also a low legibility.

In the paper by Lasota, Rossano and Shah (2014), where a participant collaborated with a robot in a virtual shared workspace to put adhesive on screws. It was shown that legible, gesture-like limb motion from the robot decreased human idle time. Thus we can assume that clear predictability of either the

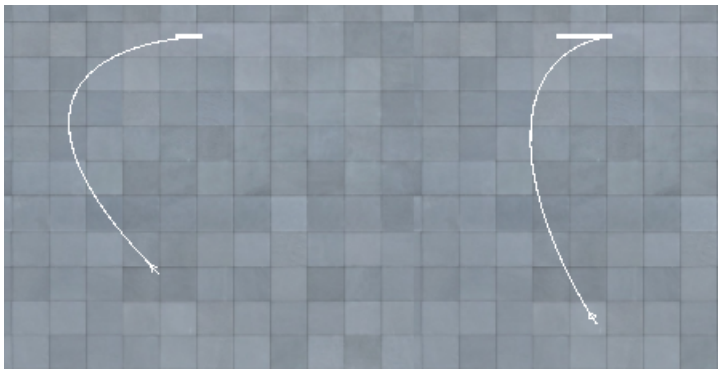


Figure 3: *Example of two different trajectories, where the left one has a larger arc, resulting in a better knowledge of the end orientation by the operator, but a lower knowledge of the end positioning, if all points on the horizontal end line can be a potential end position. On the right side, we see a trajectory where the end positioning might be easier to know, however the end orientation might not be clear*

end orientation or end positioning, through coherent movement of an AGV towards this endpoint can increase task performance. In the paper by Stulp, Grizou, Busch, and Lopes (2016) it was shown that by using reinforcement learning for the robot, based on the user preferences of predictability, that over time illegible navigation behavior from the robot was corrected to legible behavior where the navigation was slightly altered. Thus, the understanding of where the robot will end (positioning understanding), and in which orientation the robot ends (orientation understanding) is of great importance to the collaboration between a human and robot. Hence, we have to ensure that the understanding of the end orientation and end positioning is always realized, possibly resulting in an optimal understanding of the trajectory of the robot.

In this thesis, we will specifically regard the effect of different trajectories on a persons perceived message understanding (PMU) of a robot. This term was coined by Harms and Biocca (2004), referring to the ability ”of the user to understand the message being received from the ’interactant’ as well as their perception of the ’interactant’ its level of message understanding” (p. 1).

Minimum Jerk Trajectories

One element that can strongly influence the PMU of a robot, is through the implementations of minimum jerk trajectories. Outside of the literature on robotics, minimum jerk is often defined as the gradual and smooth deceleration or acceleration of joints in limbs, so that it is perceived as fluent movement (Flash & Hogan, 1985). From past HRI research, it can be shown that minimum jerk trajectories are commonly used in robotic joint movement of manipulators. These movements have been applied to an assortment of different tasks, such as hand-over tasks (Amirabdollahian, Louireiro & Harwin, 2002), or imitation movement for rehabilitation tasks (Glasauer, Huber, Basili, Knoll & Brandt, 2010), where smooth transitions between endpoints for the joints was seen as more intentful, and thus the message from the robot was easier understood. In return, it was shown from kinematic profiles that humans show minimum jerk in a hand-over task interaction with a robot which shows minimum jerk, suggesting a more smooth and social interaction profile (Quesque, Lewkowicz, Delevoye-Turrell & Coello, 2013).

It seems conceivable that the results related to the limb movements of a robot can also be applied to the navigation of an AGV. It was shown that through smooth movements an AGV can ensure its trajectory is comfortable and predictable towards the operator (see Kruse et al., 2013 for an overview). Van den Goor (2019) showed that minimum jerk trajectories can be implemented to plan a path for a humanoid robot. It was shown that when the robot would approach the human under larger angles, a minimal jerk approach had a higher perceived message understanding than when the robot used the shortest path. However, in Kruse et al. (2012), it was seen that sometimes it is more natural for an AGV to suddenly decelerate when it encounters a possible collision situation in an mobile environment. This situation is similar to how a human may decelerate when it crosses another human at a right angle to avoid

collisions. In this paper, it was shown that this type of trajectory was able to make a person understand the end position of the robot quite well, but the trajectory itself was less predictable.

In a paper by Lichtenthäler, Lorenz and Kirsch (2012) it was shown that the understanding of the end positioning of a robot, decreased with a trajectory similar to a minimum jerk trajectory. Thus, how the positioning and orientation understanding and PMU are influenced by the type of AGV trajectory, changes depending on the situation. This might be explained when we regard van den Goor (2019). Since this paper altered the end positioning, but not the end orientation, we might assume that minimum jerk trajectories only worked better because the end orientation was not varied and only the begin position and orientation was.

In some situations, it may be more important to be able to predict the positioning of an AGV, while in other situations it is more important to predict the end orientation. For example, if an operator has to ensure that they stand right across the AGV when it arrives at the endpoint, because the packages the AGV carries can only be taken off from a specific angle, this operator might be more interested in what orientation the AGV stops. However, if the operator has to ensure that they move towards the point where the AGV is moving towards and the orientation does not matter, the end positioning of the AGV might be regarded as more important.

We consider knowing both the positioning and orientation understanding to be of primary importance when interacting with any kind of automated mobile device, since we assume that these understandings are used to evaluate the PMU of the robot in terms of navigation. Furthermore, it was shown that the understanding of the end position of a robot increases the efficiency of the interaction (Guzzi, Giusti, Gambardella, Theraulaz, & Di Caro, 2013; Zhang, Sreedharan, Kulkarni, Chakraborti, Zhuo & Kambhampati, 2017), as well as the well-being of the human during the interaction (Bortot, Born & Bengler, 2013). Moreover it was shown that PMU is closely related to the acceptance (Eyssel,

Kuchenbrandt & Bobinger, 2011), approachability (Takayama, Dooley & Yu, 2011), trust (Schaefer, 2013) in/of a robot. It is thus apparent that the understanding of an AGV plays a vital role in the interaction itself and the expectations of future instances of an interaction.

Research aims

The purpose of this thesis is to examine the effects of different AGV trajectory conditions on people's PMU of the AGV's navigational goals, as indicated by the understanding of both positioning and orientation. The purpose culminated into the following research question:

How do different trajectory types of an AGV influence its perceived message understanding?

We expect that *the orientation understanding will be higher for the minimum jerk trajectories than the shortest path trajectories*. In contrast we expect that *the positioning understanding will be higher for the shortest path trajectories than the minimum jerk trajectories*. The expectations are based the work by van den Goor (2019), Scheffer (2018), and Lichtenthäler, Lorenz and Kirsch (2012). Van den Goor (2019) showed that the PMU of the robot did increase for minimum jerk trajectories under a large angle. This makes sense considering that Scheffer (2018) has shown that PMU does increase. This was confirmed in papers by Papenmeier, Uhrig, and Kirsch (2019) and Lichtenthäler, Lorenz and Kirsch (2012). In the paper by Papenmeier et al. (2019), it was shown that predictability and autonomy ratings were higher for robots with more constant angular and linear velocities compared to fluctuating velocities.

Our assumptions will be tested in an experiment where people will anticipate the end orientation and position of a robot navigating following either a minimum jerk or shortest path trajectory.

Both positioning and orientation understanding will be measured. Implicitly this will be measured by the participants performance in making clear they understand where and in which the position the robot will end up in, and explicitly we will evaluate their understanding of what the robot will do on a rating scale.

In addition, we will explore whether the explicit evaluations and the implicit measurements correlate. we are mostly interested in whether there is a correlation between implicit positioning understanding measures and the respective explicit positioning evaluation, and if implicit decision time and accuracy of the orientation understanding measures will correlate with the respective explicit orientation evaluation.

Methods

Participants and design

Based on our power analysis in G*Power, with α = 0.05, power = 0.9, effect size = 0.4299, we needed a total of 27 participants (16 male, M_{age} = 22.70, SD_{age} = 2.60, range = 18-27). This effect size was based on the results from van den Goor (2019), which had an η^2 of 0.156. The probability distribution as well as the protocol for these analyses can be found in Appendix A. Participants were recruited using the J.F. Schouten Database of Participants. This is a database for the largest part (but not exclusively) comprised of students of the Eindhoven University of Technology, where members of the database receive invites for studies through email. Participants were selected on the following criteria: they should be at least 18 years old, and speak English. They were compensated for their participation with €5.00. They received an extra €2.00 if they were not affiliated with the university.

This study has a two (AGV trajectory type: shortest path vs. minimum jerk) x two (end orientation: 0°versus 90°) x five (endpoint: -2,-1,0,1,2) within-subjects design. This accumulates in a total of twenty trials, with ten minimum jerk trajectories and ten shortest path trajectories. All trajectories can be seen in Figure 4. In the minimum jerk condition, a robot moved towards one of the five endpoints while ensuring minimal change in both angular and linear velocity, creating a very curvy trajectory, with minimal accelerations and decelerations. In the shortest path condition, the robot turned towards the orientation of the endpoint and proceeded to move towards this endpoint in a straight line. Once at the endpoint, the robot turned itself towards the right orientation. In this condition, the changes in both the angular and linear velocity are high compared to the minimum jerk condition. The specific differences between the two trajectory types as input for the robot is given in Table 1.

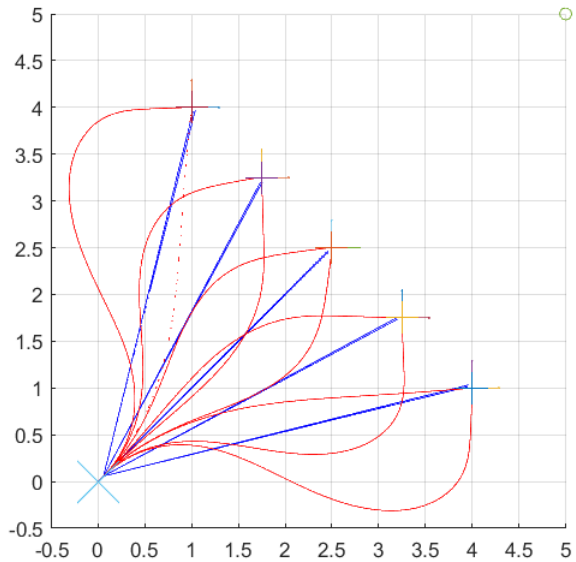


Figure 4: *Position of the robot given by the "X" sign at (0,0) on this 11 by 11 grid, with a grid size of 50 by 50 centimeters. The red lines and blue lines represent the ten minimum jerk trajectories and ten shortest path trajectories, respectively, towards the five endpoints given by the "+" signs: endpoint -2 at (1,4), endpoint -1 at (1.75,3.25) endpoint 0 (2.5,2.5), 1 at (3.25,1.75) and 2 at (4,1). The robot stops at these endpoints with two different end orientations, either in a 0 or 90 °angle from the abscissa. The start orientation of the robot is in a 45 degree from the abscissa. The start position of the participant is given by the round dot in the upper right corner at the (5,5) position. Note that the data from the dotted trajectory were omitted from further analysis due to the errors made in this trajectory*

	Minimum jerk	Shortest path
Path-planning description	Trajectory where the $\Delta\theta = \Delta\theta_{\text{min}}$ & $\Delta v = \Delta v_{\text{min}}$	Trajectory where the $T = T_{\text{min}}$
Angular velocity	$\sqrt{\frac{\theta_{(t-1)}-\theta_{(t)}}{dT}}2\sqrt{\frac{1}{cos(\theta_{(t=0)})}}$	20°/s
Linear velocity	$\sqrt{\frac{1}{cos(\theta_{(t=0)})}}\sqrt{gain*cos(\theta_{(t)})^2}+\sqrt{gain*sin(\theta_{(t)})^2}$	3m/s

Table 1: *With dT being the time derivative of 0.05 seconds, the gain*cos($\theta_{(t)}$) being the velocity in the x direction, gain*sin($\theta_{(t)}$) being velocity in the y direction, with the gain factor set at 0.2, and $\theta_{(t)}$ orientation at time t, for which the equation is given in Appendix C. And* $\sqrt{\frac{1}{cos(\theta_{(t=0)})}}$ *being the change of total distance being longer due to the endpoints not being on a circle, but on a line. The shortest path trajectory was accelerated to the maximum velocities given, with an angular acceleration of 43°/s^2 and an linear acceleration of 0.3m/s^2*

Measures

We analyzed seven measures per participant per trial. These measures include the Decision Time (DT), which measured how fast the participant was able to decide where the robot was going. To measure the DT we asked the participant to press the left mouse button for the positioning and the middle scroll wheel for the orientation. The timing with which either of the buttons was pressed was tracked and compared to our simulated robot trajectory in our python code. This timing was then divided by the total time of the trial to make it a fraction from 0 to 1. We then transformed this fraction to represent the DT performance, which is: 1-DT fraction. We will from now on refer to this DT performance as the DT.

We also measured the rate for which the participant was able to make the right decision, and how often this decision was correct, which is referred to as the accuracy. Both DT and efficiency were measured for positioning understanding, referred to as the positioning DT and positioning accuracy, and the orientation understanding, referred to as the orientation DT and orientation accuracy. We also let the participants explicitly rate the positioning and orientation understanding, as well as the PMU of the trajectory of the robot after each trial through a questionnaire consisting of one question per measurement. This self-made questionnaire can be found in Figure 5 below as well as in Appendix B.

Trial Questionnaire

After the robot has moved to its endpoint for this trial you are allowed to fill out the following three questions

* 1 How predictable is the end location of the robot?

	Very unpredictable	Unpredictable	Not unpredictable, not predictable	Predictable	Very predictable
	○	○	○	○	○

* 2 How predictable is the end orientation of the robot?

	Very unpredictable	Unpredictable	Not unpredictable, not predictable	Predictable	Very predictable
	○	○	○	○	○

* 3 How understandable was the path planning of the robot?

	Very misunderstandable	Misunderstandable	Not misunderstandable, not understandable	Understandable	Very understandable
	○	○	○	○	○

Figure 5: *The three questions used measuring the explicit positioning understanding(1), the explicit orientation understanding(2) and the perceived message understanding(3) with a 5 point Likert scale to evaluate the trajectory of the robot, used in between each trial.*

The participants were additionally questioned on their overall experience of the positioning and orientation understanding and the PMU, as well as their overall experience with robotics. Both of these questionnaires can be found in Appendix B. In addition, they were also asked to rate their general attitude towards AGVs. This attitude towards robots was measured with the negative attitudes towards robots survey (NARS), developed by Syrdal, Dautenhahn, and Koay (2009). This questionnaire had an average Cronbach's α value of 0.60 over the five questions. This low value was due to the low inter-item correlations for the third (*"I would hate the idea that robots or artificial intelligences were making judgments about things"*) and fifth item (*"I would feel uneasy if I was given a job where I had to use robots"*). However, the α value is shown to decrease when we omit these items, thus we decided to leave them all in and sum them together. The questions with each rest-item and inter-item

correlations is shown in Table 2 below, while the questionnaire itself can be found in Appendix B. In addition, we asked the participants for their age and gender which can also be found in Appendix B.

	α	IR corr	Q5	Q4	Q3	Q2	Q1
Q1: I feel that if I depend on robots too much, something bad might happen	0.470	0.496	0.088	0.282	0.545	0.318	
Q2: I am concerned that robots would be a bad influence on children	0.509	0.427	0.249	0.436	0.082		
Q3: I would hate the idea that robots or artificial intelligences were making judgments about things	0586	0.281	0.098	0.028			
Q4: I would feel very nervous just standing in front of a robot	0.544	0.362	0.196				
Q1: I would feel uneasy if I was given a job where I had to use robots	0.611	0.232					

Table 2: *Alpha values in the first column, as well as the inter-rest correlation in the second column, and the inter-item correlations between questions in the other columns for the evaluation of the negative attitudes towards robots survey, developed by Syrdal, Dautenhahn, and Koay (2009)*

Apparatus

The setup for our experiment is a combination of the setups used in van den Goor (2019) and Scheffer (2018). However, in our experiment, we added the component that the human is able to move. We made use of the Pepper Robot (Softbank Robotics, 2019) to represent the AGV in the experiment. We expected that despite its many humanoid features, it would be able to fulfill all the requirements necessary in order to compare it to a standard AGV, like the FLEET robot, as long as it kept itself in a neutral standing pose, for which only the wheels were allowed to move, while stiffening the joints to keep the Pepper robot in its neutral pose. Therefore it will make for an acceptable substitute. In order for us to make start and endpoints for the AGV as illustrated in Figure 4, a nine by nine grid was used, with a grid size of 50 by 50 centimeters. On this grid, the Pepper robot was located on the center of grid point (0,0). The robot had a start orientation of 45 degrees, in the orientation of the middle end

position (2.5,2.5). In Figure 6 the actual physical setup of these endpoints are shown.

Figure 6: *Photographs taken from the actual experimental setup where the arrows represent the combination of the robots end positioning and end orientation. In the left picture we can see one of our participants standing at the starting point on the left side, and the robot is standing on its starting point on the right side*

In addition to the Pepper robot and this grid, a wireless mouse connected to a laptop running the python code in Vizard 6, was used to register the implicit measures, through the mouse button clicks. This laptop was also used to execute the python code that moves the robot, for which the code can be found in Appendix C. A desktop was also used on which the participants were asked to fill out the online questionnaires. Moreover, the participants were video-recorded through two camera's installed in the experiment room. Two still frames from the footage taken from each of these cameras can be found in Figure 6.

The minimum jerk trajectory was continually assessed in a six by six matrix representing the change in position, velocity, and acceleration in the x and y-direction. These values ensured that the number of positions was the shortest for smallest changes in velocity and acceleration, suggesting that both changes in velocity as well as acceleration where kept to a minimum to a fifth-order degree. Once the AGV had reached its endpoint it was ensured that the end acceleration is equal to zero. This ensured

by both the angular and linear velocity being extrapolated to zero accordingly based on the heading and the distance towards the endpoint. The equation for both the x and y evaluations according to these equations is given in Appendix C as equations 1 and 2. From this evaluations the new x and y position, as well as the new orientation can be found as the inverse tangent function of the x velocity and y velocity as seen in equation 3. While the equation of the orientation for the shortest path trajectory is simply given by the inverse tangent function of the x and y position of the endpoint, which can be seen in equation 4.

Due to the fact that in the shortest path condition the robot will first turn in place, the direction the wheels are pointed in is altered. However after giving it the turn command, the wheels do not perfectly return to a position in which the direction of the wheels is pointed straight forward. This becomes problematic when next, the robot starts to move in a straight trajectory to the endpoint. Due to this deviation in wheel direction from the initiation, and the fact that the robot does not get any commands to change its angular direction until the end, the robot will sometimes had some initiation drift in the direction it had turned towards while it was still at its start point. We have counteracted this drift by having the robot move in the opposite direction, called the suppression drift. The equation for this suppression drift can be found in Appendix C, as equation 5.

Procedure

The participants were welcomed into the Virtual Reality lab in the Atlas building on the campus of the Eindhoven University of Technology. Subsequently, they were briefed about the aim of the experiment and they gave informed consent. Next, the participant was lead to the distribution floor setting. The participants had to position themselves on the human starting point. This starting point was located at the (5,5) point on the grid. Meanwhile, the AGV moved from the AGV start point: (0,0) in this

grid, towards one of five endpoints: (1,4) or (1.75,3.25) or (2.5,2.5) or (3.25,1.75) or (4,1). The robot moved to these endpoints and either ended with a 0 or 90 degree end orientation in respect to the origin. While the robot was moving towards its endpoint, the participant was allowed to freely move around within the triangle bounded by the start point (5,5), and the two outer end positions of the robot: (4,1) and (1.4). As soon as the participants were sure to which of these five endpoints and one of two ending orientations was heading, they were urged to press the button corresponding to either the end positioning or the end orientation. When both buttons were pressed by the participant, they had to move to the arrow corresponding with this end position and orientation. After the AGV arrived at its end position in the appropriate orientation, the participant had to fill out the three questions of the understanding questionnaire. This process was repeated for all 20 trials in random order. After all trials were conducted, the participant had to fill out the overall understanding questionnaire, the attitude questionnaire and the demographic questionnaire. After that, they were compensated and thanked for their participation. The whole procedure took, on average, 30 minutes to complete.

Results

In this results section we will firstly check our assumptions and examine whether there are any other effects biasing our data. Next we will present the primary results answering our research questions, after which we will present the secondary effects, which are based on some of our assumptions and the demographic data. Lastly, we will explore our results and examine what might have caused the presence and absence for our primary and secondary results.

Assumption checking and order effects

A few outliers were found that negatively affected the assumptions of normality and heteroscedasticity of the residuals, and thus we decided to drop those few unrelated values. In addition, the values connected to one trajectory (endpoint=-2, orientation=90°, trajectory type=minimum jerk) were dropped, because this trajectory deviated from its intended trajectory too many times in the experiment. But other than those issues, all necessary assumptions were met.

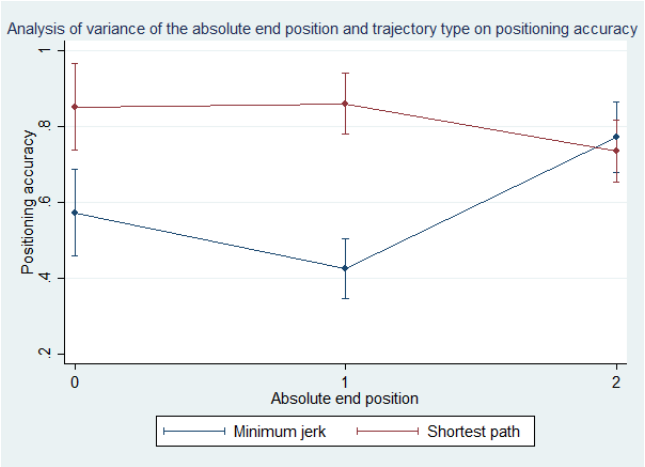
In addition, it was checked whether participants were better able to predict both the end position and end orientation over each trial. We performed four regression analyses with the trial number as the independent variable and both DT and accuracy of both positioning and orientation dependent variables. It was shown that only positioning DT showed significant increase over each trial ($\beta = 0.027, p = 0.001, R^2 = 0.023$). Thus, since participants only show a small increase in DT over the trials, which opposes our assumptions of the learning effect, this effect was disregarded in further analyses.

Primary results

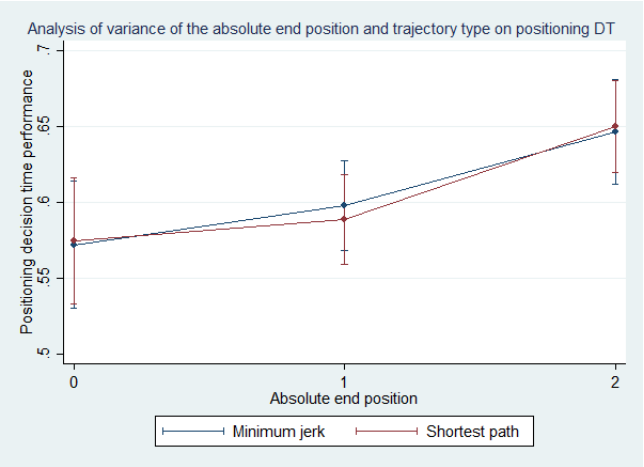
To test whether or not AGVs with minimum jerk trajectories had different values for positioning and orientation understanding, than shortest path trajectories, data on positioning accuracy and DT, orientation accuracy and DT, the explicit positioning and orientation understanding and the PMU were submitted to seven multi model analyses of variance. In the full model of the analysis we included the absolute end position of the robot (0,1,2), instead of the end position of the robot (-2,-1,0,1,2). Since it was shown that there were no difference between either the outer end positions (-2,2) or the inner end positions (-1,1) for all measures, except for a difference in trajectory type conditions for positioning understanding for the outer end positions ($F(1,509)=23.88$, $p<0.001$). Thus from now on we will refer to the absolute end position of the robot, as the end position. We also included the end orientation of the robot (0°or 90°) as a predictor, and participant ID as a covariate, and all interaction effects between the trajectory type condition and these added predictors, since we assumed that these predictors can influence the effect of the trajectory type condition. However we do not believe that the effect for the end position, might influence the effect, because all trajectories were mirrored, thus the end position should not matter between whether the robot ends in a 90°angle or a 0°angle. Thus only 7 predictors, of which 3 were an interaction effect were included in our analyses.

In this full model, the trajectory type did not influence the positioning DT, however there was an effect of the end position ($F(2,449)=9.55$, $p<0.001$, $\eta_p^2=0.046$), and an interaction effect between participant ID and trajectory type ($F(45,449)=6.88$, $p<0.001$, $\eta_p^2=0.439$) on positioning DT. Still, there was an effect of the trajectory on positioning accuracy ($F(1,509)=32.30$, $p<0.001$, $\eta_p^2=0.067$). Moreover, there was also an effect of the end position ($F(2,509)=3.41$, $p=0.034$, $\eta_p^2=0.015$), and an interaction effect between these two predictors ($F(2,509)=15.43$, $p<0.001$, $\eta_p^2=0.064$) on posi-

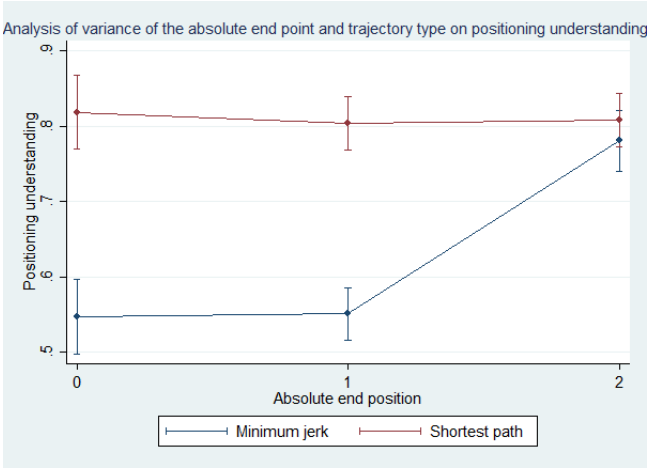
tioning accuracy. In addition, it was found that trajectory type had an effect on explicit positioning understanding, ($F(1,509)=114.74$, $p<0.001$, $\eta_p^2=0.203$), and there was an effect of end position ($F(2,509)=22.59$, $p<0.001$, $\eta_p^2=0.091$), and an interaction effect between end position and trajectory type ($F(2,509)=22.59$, $p<0.001$, $\eta_p^2=0.093$) on explicit positioning understanding. These effects are visualized in Figure 7. Thus both positioning accuracy as well as explicit positioning understanding were influenced by the trajectory type.



(a)



(b)

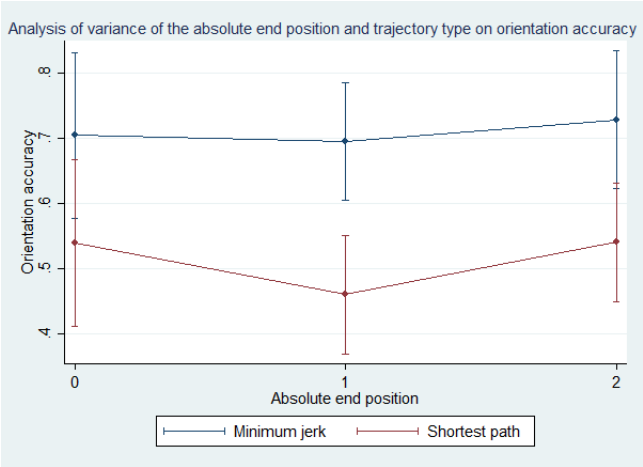


(c)

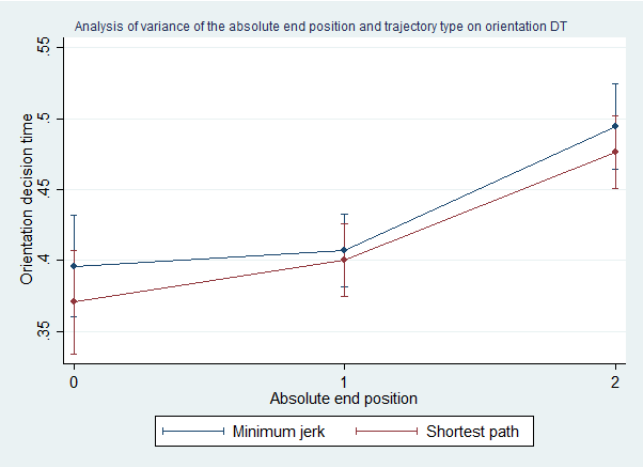
Figure 7: *Marginsplot dividing the outcomes of the positioning accuracy (a), positioning decision time (b), and explicit positioning understanding (c) over the three absolute endpoints of the robot divided as an interaction effect with the two trajectories types: minimum jerk and shortest path trajectories with 95% confidence intervals*

In the same model for orientation understanding, there was again, no effect of trajectory type on orientation DT, however there was an effect of the end position on orientation DT ($F(2,438)=25.75$, $p<0.001$, $\eta_p^2=0.118$). Similarly to positioning accuracy, there was an effect of the trajectory type on orientation

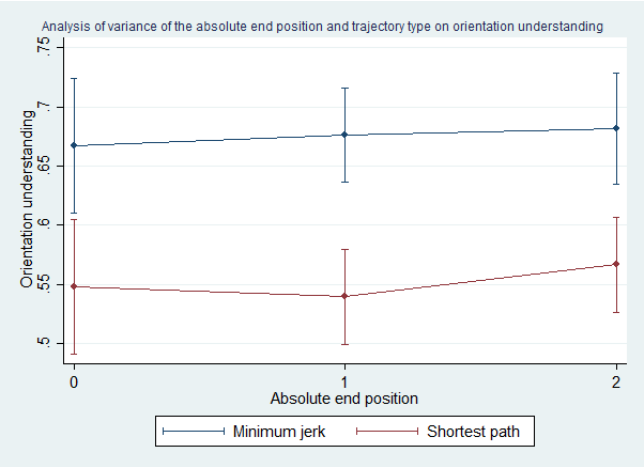
accuracy ($F(1,509)=19.66$, $p<0.001$, $\eta_p^2=0.041$). Moreover, it was found that trajectory type did significantly influence the explicit orientation understanding ($F(1,509)=39.16$, $p<0.001$, $\eta_p^2=0.080$). These effects are visualized in Figure 8. Thus both orientation accuracy and explicit orientation understanding were influenced by the trajectory type.



(a)



(b)



(c)

Figure 8: *Marginsplot dividing the outcomes of the implicit orientation accuracy (a), implicit orientation decision time (b), and explicit orientation understanding (c), over the three absolute endpoints of the robot divided as an interaction effect with the two trajectories types: minimum jerk and shortest path trajectories, with 95% confidence intervals*

In contrast to our assumptions, it was shown that both the trajectory type ($F(1,509)=58.28$, $p<0.001$, $\eta_p^2=0.115$) as well as the end position ($F(2,509)=13.48$, $p<0.001$, $\eta_p^2=0.056$), and the interaction effect between these two predictors ($F(2,509)=10.17$, $p<0.001$, $\eta_p^2=0.043$) had an effect on PMU. These

effects are visualized in Figure 9.

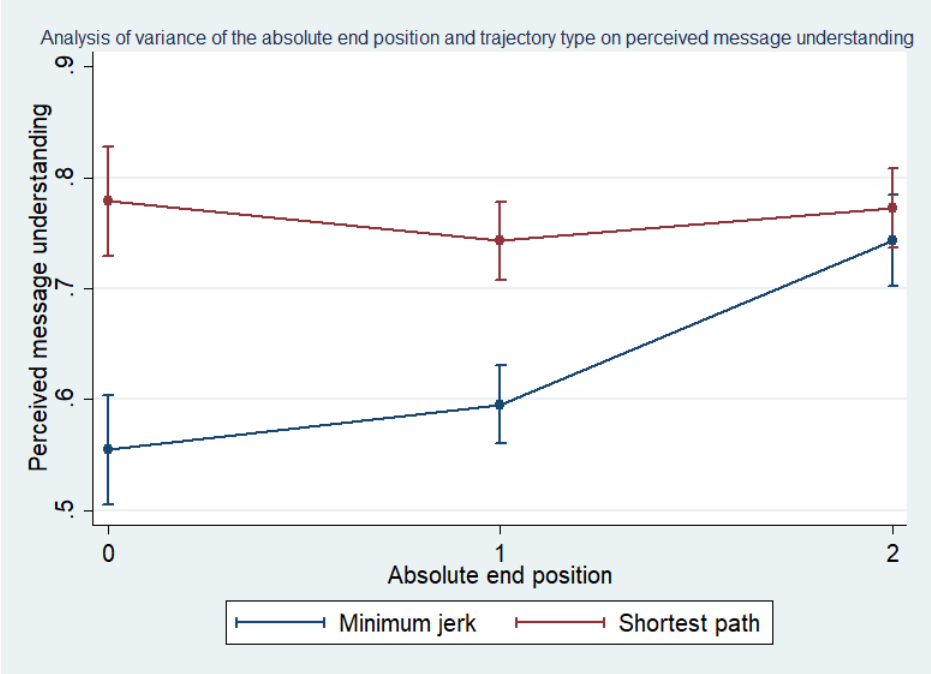


Figure 9: *Marginsplot dividing the outcomes of the PMU over the three absolute endpoints of the robot divided as an interaction effect with the two trajectories types: minimum jerk and shortest path trajectories, with 95% confidence intervals for each condition*

Secondary results

Additionally, we explored the correlation between the explicit measures to the participants explicit positioning and orientation understanding ratings from the questionnaire. Furthermore, overall positioning and orientation understanding, and overall PMU, showed small correlations towards their explicit counterparts. These correlations can be seen in Table 3. When regarding the correlations between these overall measures to the respective DT and accuracy, we examined that overall positioning understanding correlated a bit towards positioning DT(r=0.22, p<0.001) and positioning DT (r=0.14, p=0.005) and that overall orientation understanding was surprisingly enough, negatively related to the orientation

DT (r=-0.21, p<0.001). Which could imply that when the participants took longer to make a decision on the orientation, they would regard this overall longer time as a indication of better understanding in the orientation and/or vice versa.

	Positioning understanding	Orientation understanding	PMU
Positioning decision time	-	-0.129**	-
Positioning accuracy	**0.510*****	-	**0.364*****
Orientation decision time	-	0.112*	-
Orientation accuracy	-	**0.567*****	0.198***
Overall positioning understanding	0.213***	0.104*	0.128**
Overall orientation understanding	-	0.187***	-
Overall PMU	-	-	0.188***

Significance codes: * = p<0.05,** = p<0.01,*** = p<0.001

Table 3: The upper half displays the Pearson r correlations of the implicit measures compared to the explicit measures, and the lower half the Pearson r correlations of the explicit measures to the overall measures. All correlation with a r >0.3 is given in bold.

However based on the correlations in Table 3, we can assume that most participants were able to both reflect on their positioning and orientation understanding quite well. However, once we ask them on their overall understanding, they were not able to reflect on their performance as strongly.

When we regard the demographic data on our results it becomes clear that there were no effects of

gender, nor were there any effects explained by age when regarding the difference between trajectory types. Also we examined that negative attitude towards technology was barely correlated with any of these variables. Interestingly enough, it was also shown that having experience with robotics had a negative correlation with positioning accuracy (r=-0.18, p=0.008) and a similar positive correlation with implicit orientation DT (r=0.18, $p<0.001$). Moreover, for the explicit evaluations we saw an unexpected negative correlation between experience and orientation understanding (r=-0.27, $p<0.001$) and PMU (r=-0.40, $p<0.001$).

Explorative results

In the primary and secondary results it was first of all examined that positioning accuracy is higher for shortest path than minimum jerk trajectories, and that orientation accuracy is higher for minimum jerk than shortest path. Secondly, we examined that DT did not differ between trajectory types could partially be explained by the fact that both the end position and the participant ID influenced the positioning and orientation DT. Lastly, we saw that the accuracy was much more used for the evaluation of explicit positioning and orientation understanding than DT, and PMU was more related to the positioning accuracy than the orientation accuracy. In this section we will explore these three findings in more details.

Considering this first finding, it can be specifically shown that the variance in positioning accuracy and explicit positioning could be explained by the trajectory type for respectively 6.4% and 14.9%. In addition, the variance in implicit orientation accuracy and explicit orientation can be explained by the trajectory type for respectively 4.4% and 7.3%. These differences in correctness between trajectory types over the positioning of the robot at the DT are depicted in Figure 10. In this figure it can be noted that differences between trajectory types were much more pronounced, for the positioning

and orientation accuracy, compared to the positioning and orientation DT. However, contrast analyses revealed that there was only a difference in positioning accuracy between trajectory types found for the inner end position (-1,1) ($F(1,396)=11.95$, $p<0.001$) and middle position (0) ($F(1,396)=53.13$, $p<0.001$) and not found for the outer end positions (-2,2) ($F(1,396)<0.001$, $p=0.96$) and orientation accuracy was only higher for minimum jerk trajectories compared to shortest path trajectories for inner ($F(1,450)=13.12$, $p<0.001$) and outer end positions ($F(1,450)=7.02$, $p=0.008$), but not for the middle end position ($F(1,450)=3.28$ $p=0.071$). These effects show that differences for positioning become bigger for the inner end positions, and the differences for orientation become bigger for the outer end positions. Moreover, both the positioning and orientation DT, was also higher for the outer end positions, than the inner end positions (positioning: $F(1,396)=12.02$, $p<0.001$; orientation: ($F(1,385)=36.06$, $p<0.001$)), and than the middle end position (positioning: $F(1,396)=15.57$, $p<0.001$; orientation: $F(1,385)=38.58$, $p<0.001$). Thus not only was the positioning of the outer end positions easier to predict, they were also relatively earlier predicted.

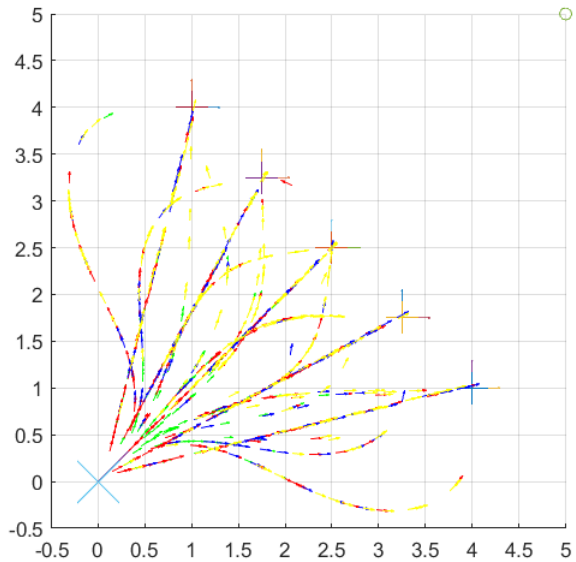


Figure 10: *Positioning and orientation of the robot at the decision time, for the trajectories for which positioning accuracy was correct (green), incorrect (red), and the orientation accuracy was correct (blue) or incorrect (yellow)*

However, both positioning and orientation DT did not generally differ between trajectory types and showed to be more nested on a participant level than the accuracy, which addresses our second finding. In the main analysis it was shown that participant ID, even as a covariate, influenced the positioning DT ($F(1,509)=4.67$, $p<0.001$, $\eta_p^2=0.009$). We thus assume that many effects are nested within the participant level itself, which can be shown by making a variable that includes both the positioning and orientation time, called understanding time. By performing a multi-level analysis of variance, it was shown that the covariance for the participant level on understanding time is $\sigma_u^2 = 0.014$ ($p<0.001$). Which is 49.34% of the total variance. However, for the understanding correctness, which is the combination of the positioning and orientation correctness, the variance nested within the participant level is 0.46% ($p=0.003$). In Figure 11 we can see that for positioning and orientation DT, there is a small intra-personal difference between trajectory types for some participants (participants 4, 8, 9, 18, 19,

20) but there is large interpersonal difference between these participants. In contrast, some participants have a large intra-personal difference (for participants 7, 10, 15, 22), however there is not much interpersonal difference between these participants. For accuracy in both positioning and orientation, only the interpersonal differences were large, but when we compared for example the accuracy of participant 1 to all other participants, not a single participant had significantly different results. This difference in how people utilize their DT differently can be examined in the interaction effect between trajectory types and participant ID on positioning DT ($F(45,449)=6.88$, $p<0.001$, $\eta_p^2=0.439$), positioning accuracy ($F(51,509)=1.38$, $p=0.050$, $\eta_p^2=0.135$), positioning understanding ($F(51,509)=2.91$, $p<0.001$, $\eta_p^2=0.248$) orientation DT ($F(45,438)=14.01$, $p<0.001$, $\eta_p^2=0.621$), orientation understanding ($F(51,509)=2,24$, $p<0.001$, $\eta_p^2=0.203$) and PMU ($F(51,509)=2.54$, $p<0.001$, $\eta_p^2=0.223$). These results reveal especially great effect sizes on DT, but smaller effects on accuracy and understanding.

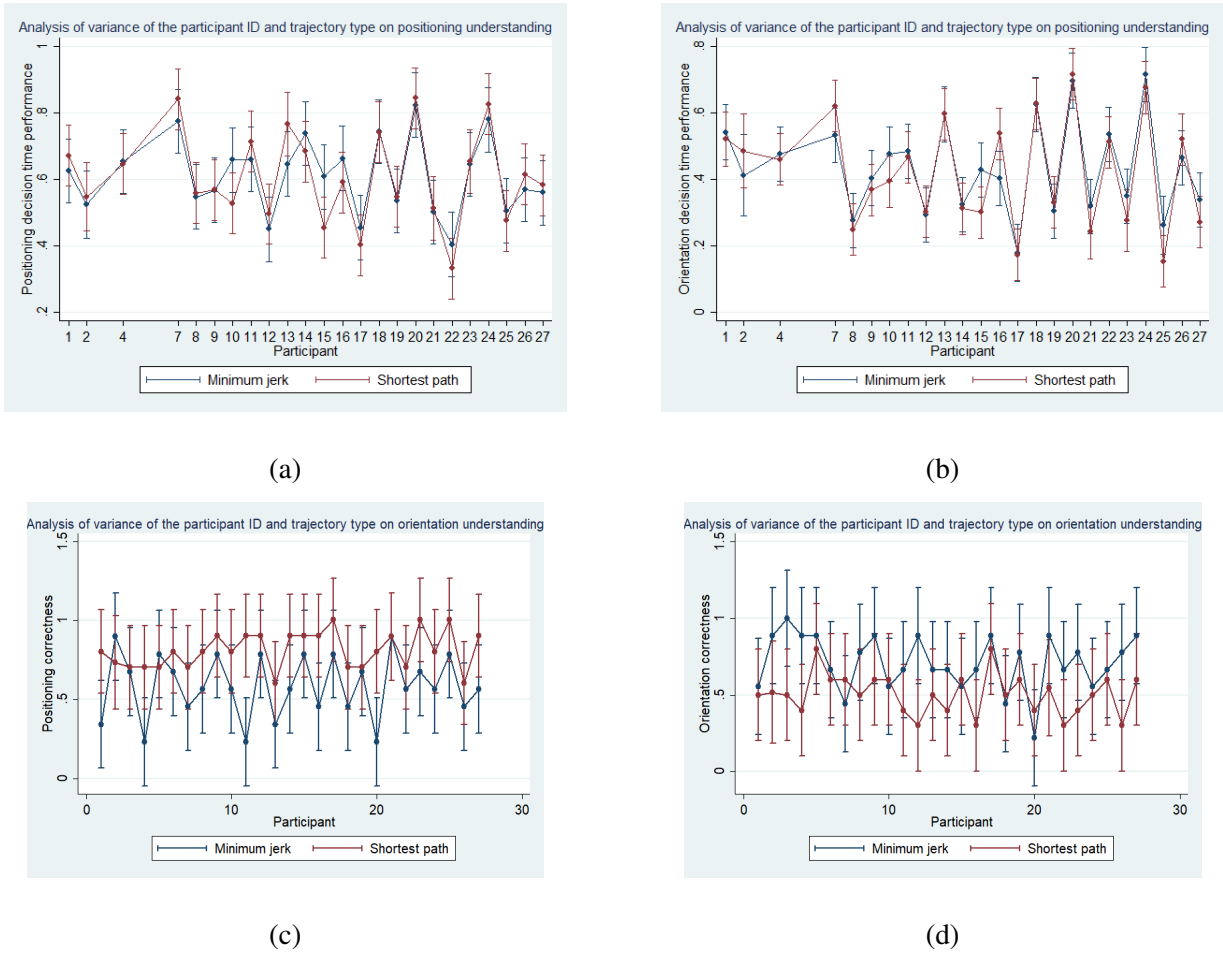


Figure 11: *Marginsplot dividing the outcomes of the positioning decision time (a) and orientation decision time (b), over the participant ID of the robot divided as an interaction effect with the two trajectories types: minimum jerk and shortest path trajectories, with 95% confidence intervals for each condition*

These large differences between DT and accuracy results, might be explained by how they are related: we examined that there is a significant correlation between DT and accuracy for both positioning (r=0.22, p<0.001), and orientation (r=0.22, p<0.001). Unsurprisingly, this correlation was positive, meaning that with increased DT, comes a better correctness of both positioning and orientation. However, it was shown that this effect is still largely nested within the participants. For positioning under-

standing, 37.10% ($p<0.001$) of the variance can be explained on the participant ID level. For orientation understanding, this nesting effect within variance for the relationship between DT and accuracy was 53.25% ($p<0.001$). We can annul the effect of nesting by regarding the average score within each participant and compare these values in a correlation between DT and accuracy. It was examined that both correlations between DT and accuracy did increase (positioning: r=0.63, $p<0.001$, orientation: r=0.75, $p<0.001$).

For our third finding, we examined a correlation between the implicit measurements of positioning and orientation understanding and their explicit counterparts in the secondary results. Unsurprisingly, the correlations from the explicit measurements of positioning and orientation understanding towards the corresponding DT were either insignificant or low, while the correlation towards the corresponding accuracy is high, as can be seen in Table 3. However, the relation between the explicit measurements and DT explained on participant ID level is low and quite similar to that of the explicit measurements and accuracy on participant ID level: 7.46% ($p<0.001$) for explicit positioning understanding and DT compared to 0.47% (p=0.008) for explicit positioning understanding and accuracy, and 0.47% ($p<0.001$) for explicit orientation understanding and DT compared to 1.01% ($p<0.001$) for explicit orientation understanding and accuracy. Interestingly enough, the correlation between explicit positioning understanding and PMU (r=0.60, $p<0.001$) was much higher than the correlation between explicit orientation understanding and PMU (r=0.25, $p<0.001$). This difference might explain why we examined a small difference in PMU between minimum jerk and shortest path, where the shortest path trajectories where regarded as more understandable than the minimum jerk trajectories: people might use the positioning of the robot more to evaluate their understanding than the orientation. Moreover, only a very small part from the effect of trajectory type on PMU was explained on a participant level (σ_u^2=0.003, p<0.001). However, PMU was substantially influenced by end position: According

to the contrast analysis on end position, the shortest path trajectory was higher in PMU than the minimum jerk trajectory for the middle end position ($F(1,450)=38.74$, $p<0.001$), and all inner end positions ($F(1,450)=33.09$, $p<0.001$), but not the outer end positions ($F(1,450)=0.99$, $p=0.320$). However, the outer end positions showed to be higher in PMU than the inner ($F(1,450)=22.43$, $p<0.001$) and middle end position ($F(1,450)=16.32$, $p<0.001$). Showing, in the same manner as position accuracy the importance of the end position, hence the moderate correlation between PMU and position accuracy ($r=0.364$, $p<0.001$).

Discussion

In this paper, human understanding of the end position and end orientation of a robot was explored, and whether this is influenced by the type of trajectory a robot navigates through. Using two time-efficient trajectory types in our experiment, we discovered a few interesting findings and gathered an insight in what is important in the movement of a robot. We will discuss the following insights and try to explain them by relaying them on the data and several other papers.

Firstly, we have seen that positioning accuracy is higher for shortest path than minimum jerk trajectories, and that orientation accuracy is higher for minimum jerk than shortest path trajectories. However, it did not seem intuitive that the orientation accuracy is also different for each end position. Especially when we regard that on average, the direction the robot was in when the orientation button was pressed, differed more from the end orientation of the robot for the outer end positions (63.07 and 52.30°) compared to the inner end positions (47.98 and 45.23°). Knowing this, we can safely state that even if the orientation at the DT is very different from the end orientation of the robot, the end orientation can be known based on the current trajectory of the robot in the minimum jerk trajectories. Especially when the endpoints are further away from the start point and are more unaligned with the starting orientation, such as the outer end positions. This makes sense for positioning understanding, considering the only alternative is either point -1 for -2 and point 1 for 2. On the other hand, shortest path trajectories, have a positioning and orientation accuracy independent of the endpoint. Thus these effects show for the orientation understanding, that for long distances which are more unaligned with the endpoint, it is better to implement minimum jerk trajectories. However, for more aligned endpoints, it does not matter for orientation understanding which trajectory is implemented. While on the contrary for the positioning understanding, these effects show that for short distances that are more aligned with the

endpoint, it is better to implement shortest path trajectories. However, for more unaligned endpoints, it does not matter for positioning understanding which trajectory is implemented.

This latter finding does not seem to be in accordance with the conclusions of van den Goor (2019). Since in this paper, the positioning accuracy in the shortest path condition seems to be much more dependent on the start position, compared to minimum jerk accuracy. However, this makes sense considering that in this paper, for the outer starting points, the angle between the two endpoints is smaller. While in our paper the angle between endpoints becomes bigger for shortest path trajectories. From these differing results, we can assume that the angle between one endpoint and a possible alternative, from the starting point, influences the positioning understanding for shortest path trajectories, but not the minimum jerk trajectories. Thus when a robot approaches an endpoint under an large angle, it might be better to implement minimum jerk trajectories. But when a robot approaches an endpoint under an small angle, it might be better to implement shortest path trajectories. This is interesting, considering that these effects make it more advantageous to implement minimum jerk trajectories in an environment which is sure to be littered with moving obstacles, such as other AGVs. If, for example, a certain AGV is heading towards an end point, for which both the positioning and orientation trajectory need to be known by the operator, it is best to just use a shortest path trajectory. However, if suddenly, another AGV moves in the way of this trajectory, the AGV needs to update its trajectory. In this situation it makes sense to use minimum jerk trajectories, considering that now the end point probably needs to be approached under a large angle, which is unaligned, thus increasing the orientation understanding with a minimum jerk trajectory. Also changing adapting a minimum jerk approach for the remainder of the trajectory will probably not influence positioning understanding compared to continuing towards the end point with a shortest path trajectory.

Secondly, we examined that DT did not differ between trajectory types which could partially be ex-

plained by the fact that both the end position and the participant ID influence the DT. We anticipated that this nesting effect within participant ID would disappear when we regarded the relation between the DT and accuracy of positioning and orientation understanding. Since it can be argued that those people that make faster decisions of how the robot will end, are often mistaken in their accuracy and vice versa. It was shown that when we compare the analysis where the effect on participant level was negated, to the effect sizes from the original analysis, all significant effects are similar in size. Thus, even if the individual effects are accounted for, there are no differences in how fast a participant is either able to establish the end positioning and orientation of a robot, between the minimum jerk and shortest path trajectories. In addition, we could not conclude that each participant uses the DT differently for their explicit evaluation of their understanding. Instead we can assume that they simply do not utilize the DT for their evaluation of the explicit understanding, even though it is moderately important for their implicit understanding.

This conclusion differs from the results found in van den Goor (2019), in which predictions about the end position of a robot were significantly faster for minimum jerk trajectories compared to shortest path trajectories. This is even more striking considering that only the end position was predicted by the participants and not the orientation understanding, which was shown to be higher for minimum jerk trajectories in our paper. However, this contradiction can be explained by the difference in setup: in van den Goor (2019) the number of starting points was manipulated, while we manipulated the number of endpoints. This suggests that it becomes harder to predict the end position of the robot with an increasing number of endpoints, which might not only explain the higher DT for the outer end positions in both papers for minimum jerk trajectories, but also the higher correctness rate for these points: in absence of many concurring possible endpoints, people will more often make the right prediction, increasing positioning understanding. Also the inclusion of predicting the end orientation

might have increased the DT on a participant level, where some participants might check, the end position first and then the end orientation and vice versa.

Lastly, we can conclude that it is better for PMU to implement shortest path trajectories, for short distances that are oriented towards the endpoint. However, for trajectories under a larger angle, it does not matter for the understanding which trajectory is used. This is, again, in contrast to the results found in van den Goor (2019) where minimum jerk trajectories had a smaller positioning DT irrespective of the end position. Though this might also be true because in this paper, the positioning was almost always predicted correctly, meaning that we might as well only analyse the positioning DT for which the positioning was correct. For this condition, an effect of trajectory type was found. Contrary to the results of van den Goor (2018), this showed a higher mean for shortest path trajectories on positioning DT than for minimum jerk trajectories. Additionally, some of these effects might be explained by Lichtenthäler, Lorenz and Kirsch (2012). Since this paper also studied the effects of the navigation of a robot on PMU, both implicitly (if participants rightly inferred the robots speed (position) and direction (orientation)) and explicitly (legibility ratings). They saw that the perceived safety was higher for shortest path trajectories than for minimum jerk trajectories, and that perceived safety was positively correlated to the robots legibility of the end position. Thus we can assume that perceived safety might play a mediating role in the effect of the trajectory type on the positioning accuracy. However in our study, the number of endpoints may have decreased the perceived safety of a minimum jerk trajectory, but not a shortest path trajectory. Whereas in a study with a low number of possible endpoints, such as van den Goor (2019) and Lichtenthäler, Lorenz and Kirsch (2012), the minimum jerk trajectory might seem safer, thus increasing the positioning accuracy.

Limitations

There are several technical, as well as methodological limitations that might have restricted or biased the outcomes of our research. For one, in this project we only used two types of robot trajectories, while other projects, such as Lichtenthäler et al. (2012), usually use many more types of trajectories. In this paper they also evaluated the waypoint follower local planner (WF). which takes the velocity and direction of the human into account while planning the trajectory. By having more trajectories, we would have gathered more reference material to which we could compare our outcomes. These other trajectories might have included a trajectory which implements both parts of the minimum jerk and of the shortest path trajectories. Where it, for example, first turns partially to the direction in line with the end position, and then moves with a constant turning velocity in an unchanging curve towards this endpoint. If this trajectory would have been taken as a reference group towards our other trajectories, we could examine more thoroughly in which situations the PMU of, for example, a minimum jerk trajectory would be higher and for which part of the trajectory it works better. However, since our design was specifically based on trajectories with large differences in both linear and angular accelerations, in which the movement of the human did not matter for the planning of the robot, we were able to disentangle effects on positioning versus orientation understanding.

We may have also been limited by the amount of surface area through which the robot can navigate, as can be seen in Figure 6. If we had used a larger surface area, the study might have been more representative of a real life distribution centre scenario, which would have increased our ecological validity. This smaller size might also have been the reason as to why participants were not urged to move around to watch the robot move. Moreover, due to this enclosed space the robot could already be clearly seen from the starting point of the participants, from which the robot is around 7 meters

removed from the participants. By inserting several obstacles that may hinder the visual field of the participants, we not only more accurately represent an environment in which these types of robots may be enforced, but we might also urge the participant to move around more. This might express more underlying behaviors for an participant. For example, participants who might be convinced that a robot will move towards a certain endpoint in a certain orientation, might be less inclined to double check whether this estimate still holds, when the robot is closer to the end goal. However, because the distance to the endpoint was quite short, we predicted that the operator would start making decisions of where the robot would end immediately, as is shown in Figure 10. Longer distances would have resulted in an unnecessary long start time for which the endpoint of the robot would not be assessed.

During the experiment we urged the participants to move towards the endpoint corresponding to the end position and orientation they judged the robot to move to, when they pressed the button for these two measures. However, it might have been the case that in some situations a participant would change their decision on for example the end positioning, once they have pressed the end orientation understanding button. In this situation they might walk towards the right endpoint, while when they pressed the positioning understanding button, they might have had a different endpoint in mind, giving a faulty estimate of their positioning DT and accuracy. Since the DT will show that they had known the end positioning much faster than they actually had, since their judgement changed. From the video recordings, it becomes clear that some participants might have indulged in this behavior: seeing as how they occasionally suddenly change their trajectory towards an endpoint, after the positioning understanding button was already pressed. One way to solve this would have been to use a button for every end position and orientation combination. However, there might be some time in-between the participant making their judgement and the participant pressing the corresponding button in this setup, delaying their judgement, to instantly get the positioning and orientation DT of the participant. Thus, we assume

that our method, despite it not being exempt from fraud, was a very accurate approach in which the accuracy and DT could be assessed.

The actual positioning of the robot during its trajectory crossing, deviated on a few trials from its virtual trajectory, from which we used our implicit measures data. Thus, the endpoint of the actual robot might be different from the point we measured, it can often be the case that the robot in one trial might have actually been in a different position or orientation than expected. The wheels of the robot do not always turn with the same frequency when the command given to the robot is to ride straight ahead, for which the turn velocity of both wheels should be equal. Also small bumps and rough edges and heterogeneity in the surface resistance on which the robot was driving, can also account for unwanted changes in linear and angular velocity of the robot. All of these random errors have fortunately been accounted by checking whether any of these effects could have possibly confused the participant in some undesirable way, by checking the video recordings made of all our trials. When we noticed that these troublesome errors resulted in confusion with the participant or when the robot arrived at the right place, the corresponding data was removed. This excluded data was mentioned in our assumption checking section. The largest unwanted change in angular velocity was the 'initiation drift', which varied between trials. Therefor, we decided to take the average over these drifts as an estimate for our suppression drift, which was able to at least partially counteract the effect of the initiation drift.

Conclusion

Ultimately, we have shown that minimum jerk trajectories allow people to more accurately predict the end orientation than shortest path trajectories, while a shortest path trajectory allows participants to more accurately predict the end position. However, comparably high effect sizes were also found for interaction effects of end position and the trajectory type condition, hence we should always keep environmental and personal preferences and tasks in mind. By including the way the operator in this environment think about the moving robot, we add knowledge to a relatively new dimension in the human robot interaction literature and support the design of understandable navigation behavior in robots. Also we anticipate that our results can be generalized and attributed to different kinds of robots in different kinds of environments, such as healthcare and social robots. Hence, transitioning towards a sortation center or airport terminal where AGVs and humans can comfortably and efficiently interact, might be close-at-hand.

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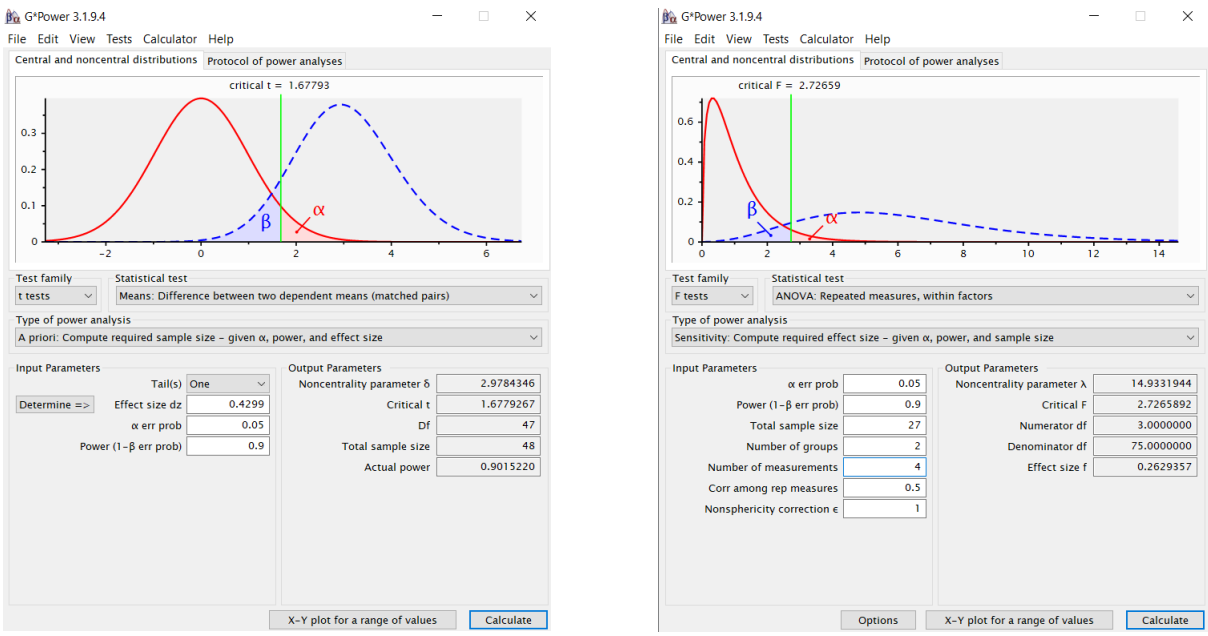
Appendix

Appendix A: G*Power Analyses



(a) (b)

Figure 12: The two G*Power analysis performed a priori for our main objective (a) and as a sensitivity test for our secondary objective (b), executed in order to know our total sample size and expected effect size f

Appendix B: Questionnaires

Understanding Questionnaire

Trial Questionnaire

After the robot has moved to its endpoint for this trial you are allowed to fill out the following three questions

* 1 How predictable is the end location of the robot?

	Very unpredictable	Unpredictable	Not unpredictable, not predictable	Predictable	Very predictable
	○	○	○	○	○

* 2 How predictable is the end orientation of the robot?

	Very unpredictable	Unpredictable	Not unpredictable, not predictable	Predictable	Very predictable
	○	○	○	○	○

* 3 How understandable was the path planning of the robot?

	Very misunderstandable	Misunderstandable	Not misunderstandable, not understandable	Understandable	Very understandable
	○	○	○	○	○

Overall Questionnaire

Overall questionnaire

Now that you are done with the trials we would like to ask you some questions about the robot during the whole experiment.

✱ 61 How predictable was the end location of the robot in general?

	Very unpredictable	Unpredictable	Not unpredictable, not predictable	Predictable	Very predictable
	○	○	○	○	○

✱ 62 How predictable was the end orientation of the robot in general?

	Very unpredictable	Unpredictable	Not unpredictable, not predictable	Predictable	Very predictable
	○	○	○	○	○

✱ 63 How understandable was the path planning of the robot in general?

	Very misunderstandable	Misunderstandable	Not misunderstandable, not understandable	Understandable	Very understandable
	○	○	○	○	○

Attitude Questionnaire

General questionnaire

In this questionnaire, we would like to know more about your opinion on robots in general. Please note your agreeability on the following statements below.

* 64 I feel that if I depend on robots too much, something bad might happen

	Entirely Disagree	Mostly Disgree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	○	○	○	○	○	○	○

* 65 I am concerned that robots would be a bad influence on children

	Entirely Disagree	Mostly Disgree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	○	○	○	○	○	○	○

* 66 I would hate the idea that robots or artificial intelligences were making judgments about things

	Entirely disagree	Mostly disagree	Somewhat disagree	Neither disagree, nor agree	Somewhat agree	Mostly agree	Entirely agree
	○	○	○	○	○	○	○

* 67 I would feel very nervous just standing in front of a robot

	Entirely Disagree	Mostly Disgree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	○	○	○	○	○	○	○

* 68 I would feel uneasy if I was given a job where I had to use robots

	Entirely Disagree	Mostly Disgree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	○	○	○	○	○	○	○

Demographic Questionnaire

Demographic information

In this section a few questions are asked specifically about you.

69 How old are you? (write down only the number)

70 What is your gender?

♀ Female | ♂ Male | ○ No answer

* 71 How much experience do you have working/cooperating with robots?

	Poor experience	Below average experience	Average experience	Above average experience	Strong experience
	○	○	○	○	○

Appendix C: Equations and Python code

x evaluation = $\mathrm{dT}_{val} \cdot M^{-1}x \Rightarrow$

$$\begin{pmatrix} p_{evalx} \\ v_{evalx} \\ \theta_{evalx} \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ tval & 1 & 0 \\ tval^2 & 2tval & 2 \\ tval^3 & 3tval^2 & 6tval \\ tval^4 & 4tval^3 & 12tval^2 \\ tval^5 & 5val^4 & 20tval^3 \end{bmatrix}^T \cdot \begin{bmatrix} 0 & t0 & t0^2 & t0^3 & t0^4 & t0^5 \\ 0 & 1 & 2t0 & 3t0^2 & 4t0^3 & 5t0^4 \\ 0 & 0 & 2 & 6t0 & 12t0^2 & 20t0^3 \\ 0 & t1 & t1^2 & t1^3 & t1^4 & t1^5 \\ 0 & 1 & 2t1 & 3t1^2 & 4t1^3 & 5t1^4 \\ 0 & 0 & 2 & 6t1 & 12t1^2 & 20t1^3 \end{bmatrix}^{-1} \begin{pmatrix} p_x \\ v_x \\ sin(a) \\ gx \\ 0 \\ endv_x \end{pmatrix} \tag{1}$$

In which first the minimum jerk matrix is updated by the new t0 and t1 value which are 0 and the minimum jerk factor, which is dependent on the distance to the goal. The inverse of this minimum jerk matrix is matrix multiplied with the current x vector. Next the dot product of the outcome is taken with the dTval for which t_{val} is the dT which is set at 0.05 seconds. This will give us the new value of the x position, the x velocity and the x orientation. With the same approach the y evaluation was updated which can be seen below.

y evaluation = $\mathrm{dT}_{val} \cdot M^{-1}y \Rightarrow$

$$\begin{pmatrix} p_{evaly} \\ v_{evaly} \\ \theta_{evaly} \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ tval & 1 & 0 \\ tval^2 & 2tval & 2 \\ tval^3 & 3tval^2 & 6tval \\ tval^4 & 4tval^3 & 12tval^2 \\ tval^5 & 5val^4 & 20tval^3 \end{bmatrix}^T \cdot \begin{bmatrix} 0 & t0 & t0^2 & t0^3 & t0^4 & t0^5 \\ 0 & 1 & 2t0 & 3t0^2 & 4t0^3 & 5t0^4 \\ 0 & 0 & 2 & 6t0 & 12t0^2 & 20t0^3 \\ 0 & t1 & t1^2 & t1^3 & t1^4 & t1^5 \\ 0 & 1 & 2t1 & 3t1^2 & 4t1^3 & 5t1^4 \\ 0 & 0 & 2 & 6t1 & 12t1^2 & 20t1^3 \end{bmatrix}^{-1} \begin{pmatrix} p_y \\ v_y \\ cos(a) \\ gy \\ 0 \\ endv_y \end{pmatrix} \tag{2}$$

Minimum jerk orientation = $\theta_{MJ(t)} \Rightarrow$

$$\arctan(\frac{v_{evalx}}{v_{evaly}})(\frac{180}{\pi}) \tag{3}$$

With v_{evalx} and v_{evaly} is the evaluation of the minimum jerk trajectory based on the equation of the x and y evaluation as seen above.

Shortest path orientation = $\theta_{SP(t)} \Rightarrow$

$$\arctan(\frac{gx}{gy})(\frac{180}{\pi}) \tag{4}$$

With gx being the x end position, with gy being the y end position.

$$Driftsuppression = \frac{driftorientation - orientation}{T} \tag{5}$$

With the drift orientation being $\arctan(\frac{gx+(dT*endpoint)}{gy-(dT*endpoint)})(\frac{180}{\pi})$ with endpoint being either -2,-1,0,1,2, and dT being the time frequency of 0.05 seconds. The orientation being $\arctan(\frac{gx}{gy})(\frac{180}{\pi})$, with gx being the x end position, with gy being the y end position. And T being the total trial time,

Python code used in Vizard 6

```
import numpy as np
import math
import matplotlib
import matplotlib.pyplot as plt
import setuptools
import pandas as pd
import nao_nocv_2_0
import naoqi
from naoqi import ALProxy
import os
import time
import re
from pynput import mouse
from pynput.keyboard import Key, Listener
from pynput import keyboard

tts = ALProxy("ALTextToSpeech","192.168.0.119", 9559)
motionProxy = ALProxy("ALMotion","192.168.0.119", 9559)
postureProxy = ALProxy("ALRobotPosture","192.168.0.119", 9559)
postureProxy.goToPosture("StandInit", 1)
motionProxy.setStiffnesses("RArm", 0.0)
motionProxy.setStiffnesses("LArm", 0.0)
#motionProxy.setExternalCollisionProtectionEnabled('All', False)
motionProxy.setOrthogonalSecurityDistance(0.002)
motionProxy.setTangentialSecurityDistance(0.002)
```

```
26
27 vrpn = viz.add('vrpn7.dle')
28 postracker = vrpn.addTracker('PPT0@hostname',0)
29 user_input = raw_input("Enter the participant number, end point, end ...
       orientation (-1=Left, 1=Right), and whether it is minimum jerk (0=Y, ...
       1=N) separated by commas:")
30
31 point, orient, mj = user_input.split(',')
32 pointn = int(point)
33 orientn = int(orient)
34 mjn = int(mj)
35
36 point = pd.DataFrame([{point}])
37 orient = pd.DataFrame([{orient}])
38 mj = pd.DataFrame([{mj}])
39
40 point.to_csv('DataX.csv', mode='a')
41 mj.to_csv('DataX.csv', mode='a')
42 orient.to_csv('DataX.csv', mode='a')
43
44 drawn = [False]*10
45 PATH, SIGHT, ARROW = 1,2,3
46
47 if mjn==0:
48     mjerk=True
49 else:
50     mjerk=False
51
```

```
52 def init():
53     global path, trialpointx, trialpointy, trialendvelx, trialendvely
54     trialpointx = 2.5+(0.75*pointn)
55     trialpointy = 2.5-(0.75*pointn)
56     if orientn==-1:
57         if pointn < 0:
58             trialendvely = -3.2*(pointn+2)+1.3
59         else:
60             trialendvely = -2.4-(0.5*pointn)
61         trialendvelx = 0
62     else:
63         if pointn ≤ 0:
64             trialendvelx = -2.4+(0.5*pointn)
65         else:
66             trialendvelx = 3.2*(pointn-2)+1.3
67         trialendvely = 0
68
69     viz.setMultiSample(4)
70     viz.fov(60)
71     ground = viz.addChild('ground.osgb')
72     viz.MainView.setPosition([0,15,0])
73     viz.MainView.setEuler([0,90,0])
74     viz.go()
75
76 def main():
77     init()
78     newTrial(trialpointx,trialpointy,trialendvelx,trialendvely)
79     x,z,dir = 0.05,0.05,0
```

```
    setState(x,z,dir)
    runExp()

def newTrial(trialpointx,trialpointy,trialendvelx,trialendvely):
    global gx, gy, state, targetorient, MT
    targetorient.x = trialendvelx
    targetorient.y = trialendvely
    state[REACHGOAL], state[FINISHED] = False,False
    clearDrawing()
    gx, gy = trialpointx, trialpointy

    # Plot new goal point
    viz.startlayer(viz.LINES)
    viz.linewidth(3)
    viz.vertex(gx,0.01,gy)
    viz.vertex(gx+targetorient.x*.05,0.01,gy+targetorient.y*.05)
    gl = viz.endlayer()

def initObstacles():
    if __name__ == "__main__":
        create_map()
    h = 0.05
    for ob in obstacles:
        box = viz.addChild('crate.osgb',cache=viz.CACHE_COPY)
        xl = ob[2]-ob[0]
        yl = ob[3]-ob[1]
        box.setScale([xl,h,yl])
        box.setPosition([ob[0]+0.5*xl,h*0.5,ob[1]+0.5*yl])
```

```
def runExp():
    viz.callback(viz.TIMER_EVENT,testLoop)
    viz.starttimer(1, 1.0/60,viz.PERPETUAL)

def testLoop(a):
    finish, d = stepTrial()
    if finish:
        viz.killtimer(1)
        #print(viz.starttimer)

x, y = 0, 0
override_dir = None

def setState(px=0,py=0,pdir=0):
    global x,y,direction,override_dir
    if not (px == 0 and py == 0):
        x, y = px, py
    override_dir = None
    if not pdir == 0:
        direction = pdir
        override_dir = pdir

state = [False]*3
REACHGOAL, FINISHED = 0,1

def stepTrial(px=0,py=0,pdir=0):
    global state
```

```
    setState(px,py,pdir)
    if not state[REACHGOAL]:
        update_path(0)
    return state[FINISHED], direction

def update_path(a):
    global T, os, direction, obs_map, x, y, gx, gy, slx, sly, srx, sry, ...
        steer, mjerk, MT, velx, vely, df2, rotation, targetdir, avec, bvec, ...
        dist, gain, con, on_click
    gain = 0.2
    dT = 0.05
    T = T + dT
    rng = 0.11
    ang = np.radians(30)
    a = np.radians(direction)
    targetdir = (1+orientn)*45
    velx = np.sin(a)*gain
    vely = np.cos(a)*gain
    dirold = direction
    ddir = dirold - direction
    direction = np.arctan2(gx,gy)*180/np.pi
    drift = dT*pointn
    driftdirection = np.arctan2(gx+drift,gy-drift)*180/np.pi
    trialperiod = (15+((pointn**2)*0.75))/dT
    driftsup = (driftdirection - direction)/trialperiod
    rotation = targetdir - direction
    startdir = 45-np.arctan2(gx,gy)*180/np.pi
    vel = ...
```

```
        (math.sqrt(1/(math.cos(np.radians(startdir)))))*(math.sqrt((velx**2)+(vely**2)))
    if pointn != 0:
        simdif = ...
            (np.arctan2(gx,gy)*180/np.pi-np.arctan2(gx+0.5,gy-0.5)*180/np.pi)/pointn
    else:
        simdif = 0

    if mjerk==False:

        #simulated motion
        xtstart = np.array([0,x,velx,np.sin(a)])
        ytstart = np.array([0,y,vely,np.cos(a)])
        xtstop = np.array([MT,gx,0,targetorient.x])
        ytstop = np.array([MT,gy,0,targetorient.y])
        avec = minjerk(xtstart,xtstop)
        bvec = minjerk(ytstart,ytstop)
        tt1 = evaljerk(avec,dT)
        tt2 = evaljerk(bvec,dT)
        x = tt1[0]
        y = tt2[0]
        xoff = trialpointx-x
        yoff = trialpointy-y
        dist = math.sqrt((gy-y)**2+(gx-x)**2)

        #real motion
        if con == True:
            motionProxy.moveTo(0, 0, np.radians(startdir+simdif))
            time.sleep(1)
```

```
            con=False
        motionProxy.move(vel, 0, driftsup)

    if mjerk==True:

        #simulated motion
        xtstart = np.array([0,x,velx,np.sin(a)])
        ytstart = np.array([0,y,vely,np.cos(a)])
        xtstop = np.array([MT,gx,0,targetorient.x])
        ytstop = np.array([MT,gy,0,targetorient.y])
        avec = minjerk(xtstart,xtstop)
        bvec = minjerk(ytstart,ytstop)
        ox = x
        oy = y
        tt1 = evaljerk(avec,dT)
        tt2 = evaljerk(bvec,dT)
        x = tt1[0]
        y = tt2[0]
        dist = math.sqrt((gy-y)**2 + (gx-x)**2)
        if  dist < 6.0 and MT > 0.5:
            MT = max(dist*1.5, 0.5)
        direction = (np.arctan2(tt1[1],tt2[1])*180/np.pi)
        ddir = dirold - direction
        rotation = targetdir - direction

        #real motion
        if con == True:
            time.sleep(1)
```

```
            con=False
        motionProxy.move(vel, 0, ...
            np.radians((ddir/dT)/(math.sqrt(1/(math.cos(np.radians(startdir)))))))
    df = ...
        pd.DataFrame({'T':[T],'dist':[dist],'direction':[direction],'x':[x],'y':[y]})#,'or
    print(df)

    if dist > 0.05 or (dist > 0.1 and not mjerk):
        display()

    else:
        global state
        state[REACHGOAL] = True
        if mjerk==False:
            if rotation ≤ 180:
                motionProxy.moveTo(0, 0, ...
                    np.radians(-rotation+simdif))#-simdif))
            if rotation ≥ 180:
                motionProxy.moveTo(0, 0, ...
                    np.radians(360-rotation+simdif))#-simdif))
            time.sleep(3)
        if mjerk: state[FINISHED] = True
        motionProxy.move(0, 0, 0)
        print("Reached the goal")
        #postureProxy.goToPosture("Crouch")
        x = pd.to_numeric(df2)
        x = list(map(int, x))
        plt.plot(x, y)
```

```
        plt.xlabel('x axis')
        plt.ylabel('y axis')
        plt.title('Positioning of AGV')
        plt.grid(True)
        return plt.savefig("Vizard_Plot.pdf", format='pdf')

def getReachedgoal():
    return state[REACHGOAL]

def rotate(a):
    global direction, state
    targetdir = np.arctan2(targetorient.x,targetorient.y)*180/np.pi+180
    #if targetdir > 360: targetdir-=360
    targetdir = targetdir % 360
    direction = direction % 360
    rotation = (targetdir - direction) % 360
    #if targetdir > direction:
    if rotation > 180:
        direction -= 3
    #elif targetdir < direction:
    elif rotation ≤ 180:
        direction += 3

def clearDrawing():
    global path, sight, drawn
    if drawn[PATH]:
        path.remove()
    if drawn[SIGHT]:
```

```
        sight.clearVertices()
count = 1

def plotPoint(y):
    global count
    viz.startLayer(viz.LINES)
    viz.vertexColor(1,0,0)
    viz.vertex(y,0.03,count)
    count-=.002
    viz.vertex(y ,0.03,count-.008)
    p = viz.endLayer()

def plotPath(x,y,gx,gy,dir):
    global path, sight, drawn, gain
    if drawn[PATH]:
        path.remove()
    if drawn[SIGHT]:
        sight.clearVertices()
    it = 0
    dist = math.sqrt((gy-y)**2 + (gx-x)**2)
    a = np.radians(dir)
    viz.startLayer(viz.LINES)
    viz.vertex(x,0.01,y)
    dT = 0.08
    nj = np.floor(MT/dT)
    for i in range (0,int(nj)):
        xp = evaljerk(avec,i*dT)
        yp = evaljerk(bvec,i*dT)
```

```
        viz.vertex(xp[0],0.01,yp[0])
        viz.vertex(xp[0],0.01,yp[0])
        it+=1
    path = viz.endLayer()
    drawn[PATH] = True

def minjerk(xtstart,xtstop):
    t0=xtstart[0]
    t1=xtstop[0]
    tmat=np.mat(   [[ 1, t0, t0**2, t0**3 , t0**4 ,t0**5],
                      [0, 1,  2*t0, 3*t0**2, 4*t0**3,  5*t0**4],
                      [0, 0,  2,    6*t0,   12*t0**2, 20*t0**3],
                      [1, t1, t1**2, t1**3,   t1**4 ,   t1**5],
                      [0, 1,  2*t1, 3*t1**2, 4*t1**3,  5*t1**4],
                      [0, 0,  2,    6*t1,   12*t1**2, 20*t1**3]])
    xvec = np.append(xtstart[1:4], xtstop[1:4])
    avec = np.linalg.solve(tmat,xvec)
    return avec

def evaljerk(avec,tval):
    tmat=np.array([[1, tval, tval**2, tval**3,   tval**4,    tval**5],
                     [0, 1,    2*tval, 3*tval**2, 4*tval**3,  5*tval**4],
                     [0, 0,    2,      6*tval,   12*tval**2, 20*tval**3]]) ...
                        #% ...
    #       0 0    0      6        24*tval   60*tval^2; ...
    #       0 0    0      0        24        120*tval; ...
    #       0 0    0      0        0         120];
    xtval=np.dot(tmat,avec)
```

```
    return xtval


def detect_obs(x,y,obs_map):
    sz = len(obs_map)
    absx = int(np.round(x*(0.5*sz)+0.5*sz,0))
    absy = int(np.round(y*(0.5*sz)+0.5*sz,0))

    if absx > sz-1:
        absx = sz-1
    elif absx < 0:
        absx = 0
    if absy > sz-1:
        absy = sz-1
    elif absy < 0:
        absy = 0
    return obs_map[absx,absy]


def create_map():
    global obs_map
    sz = len(obs_map)

    obs_list = (obstacles+1)*0.5*sz #obstacles*50 + 50
    for obs1_map in obs_list:
        for x in range(0,int(obs1_map[2]-obs1_map[0])):
            for y in range (0,int(obs1_map[3]-obs1_map[1])):
                posx = int(x+obs1_map[0])
```

```
                posy = int(y+obs1_map[1])
                obs_map[posx,posy] = 1
                1
def display():
    global drawn, sight, arrow, override_dir
    viz.vertexColor(0,0.6,0)
    if drawn[SIGHT]: sight.clearVertices()
    viz.startlayer(viz.POINTS)
    viz.vertexColor(0.6,0,0)
    viz.pointsize(3)
    viz.vertex(slx,0.011,sly)
    viz.vertex(srx,0.011,sry)
    sight = viz.endlayer()
    drawn[SIGHT] = True
    viz.vertexColor(0,0.6,0)
    viz.lineWidth(2)

    if not drawn[ARROW]:
        viz.startlayer(viz.LINES)
        viz.vertex(-0.03,0,0)
        viz.vertex(0,0,0.06)
        viz.vertex(0.03,0,0)
        viz.vertex(0,0,0.06)
        viz.vertex(0,0,0.06)
        viz.vertex(0,0,-0.06)
        arrow = viz.endlayer()
        drawn[ARROW] = True
    if override_dir == None:
```

```
        arrow.setEuler(direction)
    else:
        arrow.setEuler(override_dir)
    arrow.setPosition([x,0.01,y])
    if not state[REACHGOAL]:
        plotPath(x,y,gx,gy,direction)
    return

def getState():
    return x,y,direction

class pos(object):
    def __init__(self,x,y,vx,vy):
        pos.x = x
        pos.y = y
        pos.velx = vx
        pos.vely = vy

targetorient = pos(0,1,-90,-90)
T = 0
pos = 0
x,y = 0,0
slx,sly,srx,sry = 0,0,0,0
MT = 4
direction = 45
steer = 0
Frequency = 0.3
con=True
```

```
obs_map = np.empty([1000,1000])
np.arctan2(0,1)*180/np.pi
obstacles = np.array([[-0.8,-0.2, -0.2, 0.8],
                      [-0.2,0.4, 0.3, 0.8],
                      [0.2,-1, 1, 0]])
obstacles = np.array([[-0.15,-0.4,0.15,0.2]])
obstacles = np.array([[-0.4,-0.15,0.4,0.15]])

if __name__ == '__main__': main()
```